RFM based Customer Segmentation and ARIMA Sales Forecasting

BY – Devika Talla

```
import pandas as pd

# Load the Excel file
file_path = 'data.xlsx'

# Load each sheet into a DataFrame
df_2009_2010 = pd.read_excel(file_path, sheet_name='Year 2009-2010')
df_2010_2011 = pd.read_excel(file_path, sheet_name='Year 2010-2011')

# Combine the DataFrames
df = pd.concat([df_2009_2010, df_2010_2011])

# Reset the index if needed
df.reset_index(drop=True, inplace=True)

# Display the combined DataFrame
print(df.head())
```

```
  Invoice StockCode                          Description  Quantity  \
0  489434     85048  15CM CHRISTMAS GLASS BALL 20 LIGHTS        12
1  489434    79323P                   PINK CHERRY LIGHTS        12
2  489434    79323W                  WHITE CHERRY LIGHTS        12
3  489434     22041         RECORD FRAME 7" SINGLE SIZE         48
4  489434     21232       STRAWBERRY CERAMIC TRINKET BOX        24

          InvoiceDate  Price  Customer ID         Country
0 2009-12-01 07:45:00   6.95      13085.0  United Kingdom
1 2009-12-01 07:45:00   6.75      13085.0  United Kingdom
2 2009-12-01 07:45:00   6.75      13085.0  United Kingdom
3 2009-12-01 07:45:00   2.10      13085.0  United Kingdom
4 2009-12-01 07:45:00   1.25      13085.0  United Kingdom
```

```
df.dtypes
```

```
Invoice                object
StockCode              object
Description            object
Quantity                int64
InvoiceDate    datetime64[ns]
Price                 float64
Customer ID           float64
Country                object
dtype: object
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1067371 entries, 0 to 1067370
Data columns (total 8 columns):
 #   Column       Non-Null Count    Dtype         
---  ------       --------------    -----         
 0   Invoice      1067371 non-null  object        
 1   StockCode    1067371 non-null  object        
 2   Description  1062989 non-null  object        
 3   Quantity     1067371 non-null  int64         
 4   InvoiceDate  1067371 non-null  datetime64[ns]
 5   Price        1067371 non-null  float64       
 6   Customer ID  824364 non-null   float64       
 7   Country      1067371 non-null  object        
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 65.1+ MB
```

Understanding the dataset

In this dataset we have the following rows

1. InvoiceNo: Invoice number.
2. StockCode: Product (item) code. Nominal. A 5-digit integral number uniquely assigned to each distinct product.
3. Description: Product (item) name. Nominal.
4. Quantity: The quantities of each product (item) per transaction. Numeric.
5. InvoiceDate: Invoice date and time. Numeric. The day and time when a transaction was generated.
6. UnitPrice: Unit price. Numeric. Product price per unit in sterling (Â£).
7. CustomerID: Customer number. Nominal. A 5-digit integral number uniquely assigned to each customer.
8. Country: Country name. Nominal. The name of the country where a customer resides.

```
#Checking missing values
df.isna().sum()
```

```
Invoice           0
StockCode         0
Description    4382
Quantity          0
InvoiceDate       0
```

```
Price                0
Customer ID     243007
Country              0

dtype: int64
```

Here we can see that the 'Description' and 'Customer ID' columns have null values.

```
#Handling missing values
df.dropna(subset = ['Customer ID'], axis=0, inplace = True)
print(f'Shape after removing null values from the dataset : {df.shape}')

Shape after removing null values from the dataset : (824364, 8)

df.isna().sum()

Invoice        0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
Price          0
Customer ID    0
Country        0

dtype: int64
```

There are no missing values now.

```
#Checking negative values
df.describe()
```

	Quantity	Price	Customer ID
count	824364.000000	824364.000000	824364.000000
mean	12.414574	3.676800	15324.638504
std	188.976099	70.241388	1697.464450
min	-80995.000000	0.000000	12346.000000
25%	2.000000	1.250000	13975.000000
50%	5.000000	1.950000	15255.000000
75%	12.000000	3.750000	16797.000000
max	80995.000000	38970.000000	18287.000000

The above table indicated there are negative values in the 'Quantity' and 'Price' column. We'll have to remove those as these indicate cancelled or returned products

```
#Columns having negative values
df[(df['Quantity']<= 0)]
```

```
         Invoice StockCode                          Description  Quantity  \
178      C489449     22087             PAPER BUNTING WHITE LACE       -12
179      C489449    85206A         CREAM FELT EASTER EGG BASKET        -6
180      C489449     21895       POTTING SHED SOW 'N' GROW SET        -4
181      C489449     21896                  POTTING SHED TWINE        -6
182      C489449     22083           PAPER CHAIN KIT RETRO SPOT       -12
...          ...       ...                                  ...       ...
1065910  C581490     23144      ZINC T-LIGHT HOLDER STARS SMALL       -11
1067002  C581499         M                               Manual        -1
1067176  C581568     21258           VICTORIAN SEWING BOX LARGE        -5
1067177  C581569     84978     HANGING HEART JAR T-LIGHT HOLDER        -1
1067178  C581569     20979        36 PENCILS TUBE RED RETROSPOT        -5

                InvoiceDate   Price  Customer ID         Country
178     2009-12-01 10:33:00    2.95      16321.0       Australia
179     2009-12-01 10:33:00    1.65      16321.0       Australia
180     2009-12-01 10:33:00    4.25      16321.0       Australia
181     2009-12-01 10:33:00    2.10      16321.0       Australia
182     2009-12-01 10:33:00    2.95      16321.0       Australia
...                     ...     ...          ...             ...
1065910 2011-12-09 09:57:00    0.83      14397.0  United Kingdom
1067002 2011-12-09 10:28:00  224.69      15498.0  United Kingdom
1067176 2011-12-09 11:57:00   10.95      15311.0  United Kingdom
1067177 2011-12-09 11:58:00    1.25      17315.0  United Kingdom
1067178 2011-12-09 11:58:00    1.25      17315.0  United Kingdom

[18744 rows x 8 columns]
```

```
df['Invoice'].str.contains('C').sum()
```

```
18744
```

```
df = df[~df['Invoice'].str.contains('C', na=False)]
df
```

```
        Invoice StockCode                          Description  Quantity  \
0        489434     85048  15CM CHRISTMAS GLASS BALL 20 LIGHTS        12
1        489434    79323P                   PINK CHERRY LIGHTS        12
2        489434    79323W                  WHITE CHERRY LIGHTS        12
3        489434     22041         RECORD FRAME 7" SINGLE SIZE         48
4        489434     21232       STRAWBERRY CERAMIC TRINKET BOX        24
```

```
...          ...       ...                                ...        ...
1067366  581587     22899        CHILDREN'S APRON DOLLY GIRL         6
1067367  581587     23254       CHILDRENS CUTLERY DOLLY GIRL         4
1067368  581587     23255     CHILDRENS CUTLERY CIRCUS PARADE        4
1067369  581587     22138       BAKING SET 9 PIECE RETROSPOT         3
1067370  581587      POST                              POSTAGE        1

                InvoiceDate  Price  Customer ID         Country
0       2009-12-01 07:45:00   6.95      13085.0  United Kingdom
1       2009-12-01 07:45:00   6.75      13085.0  United Kingdom
2       2009-12-01 07:45:00   6.75      13085.0  United Kingdom
3       2009-12-01 07:45:00   2.10      13085.0  United Kingdom
4       2009-12-01 07:45:00   1.25      13085.0  United Kingdom
...                     ...    ...          ...             ...
1067366 2011-12-09 12:50:00   2.10      12680.0          France
1067367 2011-12-09 12:50:00   4.15      12680.0          France
1067368 2011-12-09 12:50:00   4.15      12680.0          France
1067369 2011-12-09 12:50:00   4.95      12680.0          France
1067370 2011-12-09 12:50:00  18.00      12680.0          France

[805620 rows x 8 columns]
```

```
df['Description'] = df['Description'].str.strip()
```

```
#Remove duplicate values
df.duplicated().sum()
```

```
26125
```

```
df = df.drop_duplicates()
df.duplicated().sum()
```

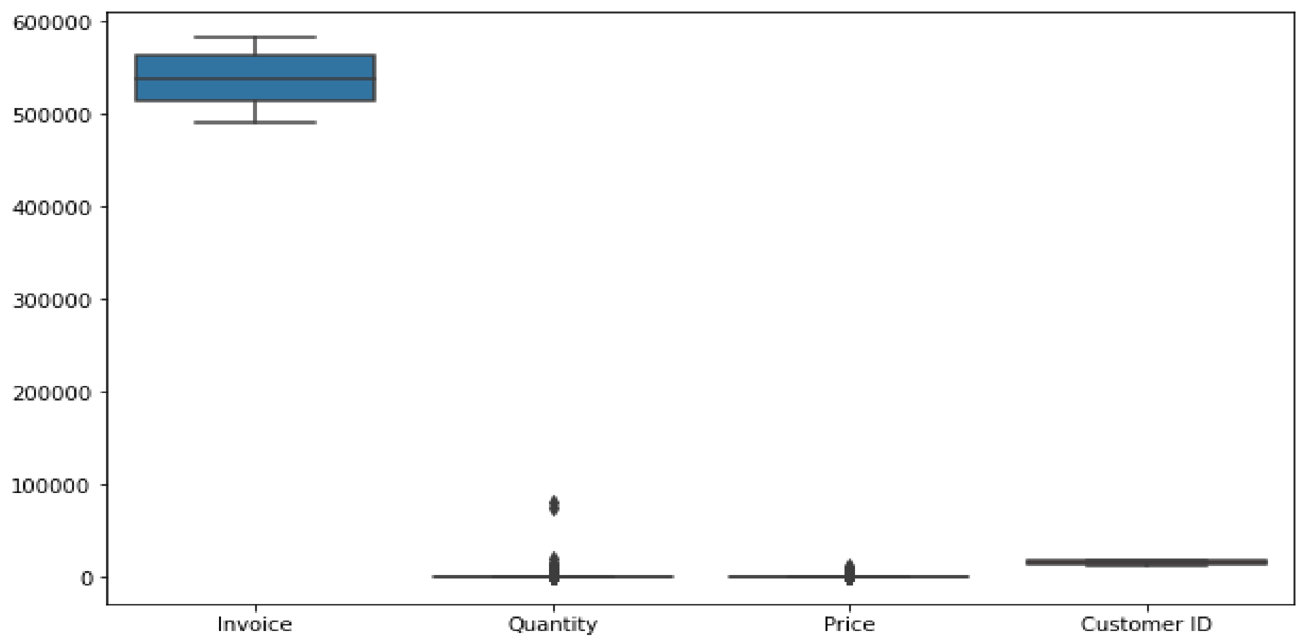
```
0
```

```
df
```

```
        Invoice StockCode                          Description  Quantity  \
0        489434     85048  15CM CHRISTMAS GLASS BALL 20 LIGHTS        12
1        489434    79323P                   PINK CHERRY LIGHTS        12
2        489434    79323W                  WHITE CHERRY LIGHTS        12
3        489434     22041         RECORD FRAME 7" SINGLE SIZE         48
4        489434     21232       STRAWBERRY CERAMIC TRINKET BOX        24
...          ...       ...                                  ...       ...
1067366  581587     22899          CHILDREN'S APRON DOLLY GIRL         6
1067367  581587     23254         CHILDRENS CUTLERY DOLLY GIRL         4
1067368  581587     23255      CHILDRENS CUTLERY CIRCUS PARADE         4
1067369  581587     22138         BAKING SET 9 PIECE RETROSPOT         3
1067370  581587      POST                              POSTAGE         1

                InvoiceDate  Price  Customer ID         Country
0       2009-12-01 07:45:00   6.95      13085.0  United Kingdom
```

```
1       2009-12-01 07:45:00   6.75      13085.0  United Kingdom
2       2009-12-01 07:45:00   6.75      13085.0  United Kingdom
3       2009-12-01 07:45:00   2.10      13085.0  United Kingdom
4       2009-12-01 07:45:00   1.25      13085.0  United Kingdom
...                     ...    ...          ...             ...
1067366 2011-12-09 12:50:00   2.10      12680.0          France
1067367 2011-12-09 12:50:00   4.15      12680.0          France
1067368 2011-12-09 12:50:00   4.15      12680.0          France
1067369 2011-12-09 12:50:00   4.95      12680.0          France
1067370 2011-12-09 12:50:00  18.00      12680.0          France

[779495 rows x 8 columns]
```

```python
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd

#Check for Outliers
plt.figure(figsize=(10,6))
sns.boxplot(data = df)
plt.show()
```




```python
#We will remove the extreme outliers
Q1 = df[['Quantity', 'Price']].quantile(0.01)
Q3 = df[['Quantity', 'Price']].quantile(0.99)
IQR = Q3 - Q1

df_outliers = df[((df[['Quantity', 'Price']] < (Q1 - 1.5 * IQR)) |
(df[['Quantity', 'Price']] > (Q3 + 1.5 * IQR))).any(axis=1)]
```

```
df_outliers
```

```
        Invoice StockCode                     Description  Quantity  \
126      489444      POST                         POSTAGE         1   
173      489447      POST                         POSTAGE         1   
217      489460     84598  BOYS ALPHABET IRON ON PATCHES       576   
575      489523     84879  ASSORTED COLOUR BIRD ORNAMENT       800   
1344     489562     84472   PINK AND LILAC QUILTED THROW         1   
...         ...       ...                             ...       ...   
1063344  581375     21137        BLACK RECORD COVER FRAME       960   
1065522  581457     23543            WALL ART KEEP CALM       698   
1065531  581458     22197                 POPCORN HOLDER      1500   
1065532  581459     22197                 POPCORN HOLDER      1200   
1065882  581483     23843    PAPER CRAFT , LITTLE BIRDIE     80995   

                InvoiceDate   Price  Customer ID         Country  
126     2009-12-01 09:55:00  141.00      12636.0             USA  
173     2009-12-01 10:10:00  130.00      12362.0         Belgium  
217     2009-12-01 10:46:00    0.21      16167.0  United Kingdom  
575     2009-12-01 11:46:00    1.45      12931.0  United Kingdom  
1344    2009-12-01 13:07:00   45.95      17998.0  United Kingdom  
...                     ...     ...          ...             ...  
1063344 2011-12-08 12:36:00    3.39      16210.0  United Kingdom  
1065522 2011-12-08 18:43:00    4.15      18102.0  United Kingdom  
1065531 2011-12-08 18:45:00    0.72      17949.0  United Kingdom  
1065532 2011-12-08 18:46:00    0.72      17949.0  United Kingdom  
1065882 2011-12-09 09:15:00    2.08      16446.0  United Kingdom  

[3104 rows x 8 columns]
```

```
df = df.drop(df_outliers.index)
df
```

```
        Invoice StockCode                          Description  Quantity  \
0        489434     85048  15CM CHRISTMAS GLASS BALL 20 LIGHTS        12   
1        489434    79323P                   PINK CHERRY LIGHTS        12   
2        489434    79323W                  WHITE CHERRY LIGHTS        12   
3        489434     22041         RECORD FRAME 7" SINGLE SIZE         48   
4        489434     21232       STRAWBERRY CERAMIC TRINKET BOX        24   
...         ...       ...                                  ...       ...   
1067366  581587     22899         CHILDREN'S APRON DOLLY GIRL          6   
1067367  581587     23254        CHILDRENS CUTLERY DOLLY GIRL          4   
1067368  581587     23255      CHILDRENS CUTLERY CIRCUS PARADE          4   
1067369  581587     22138        BAKING SET 9 PIECE RETROSPOT          3   
1067370  581587      POST                              POSTAGE         1   

                InvoiceDate  Price  Customer ID         Country  
0       2009-12-01 07:45:00   6.95      13085.0  United Kingdom  
1       2009-12-01 07:45:00   6.75      13085.0  United Kingdom  
2       2009-12-01 07:45:00   6.75      13085.0  United Kingdom  
```

```
3       2009-12-01 07:45:00   2.10      13085.0  United Kingdom
4       2009-12-01 07:45:00   1.25      13085.0  United Kingdom
...                     ...    ...          ...             ...
1067366 2011-12-09 12:50:00   2.10      12680.0          France
1067367 2011-12-09 12:50:00   4.15      12680.0          France
1067368 2011-12-09 12:50:00   4.15      12680.0          France
1067369 2011-12-09 12:50:00   4.95      12680.0          France
1067370 2011-12-09 12:50:00  18.00      12680.0          France

[776391 rows x 8 columns]
```

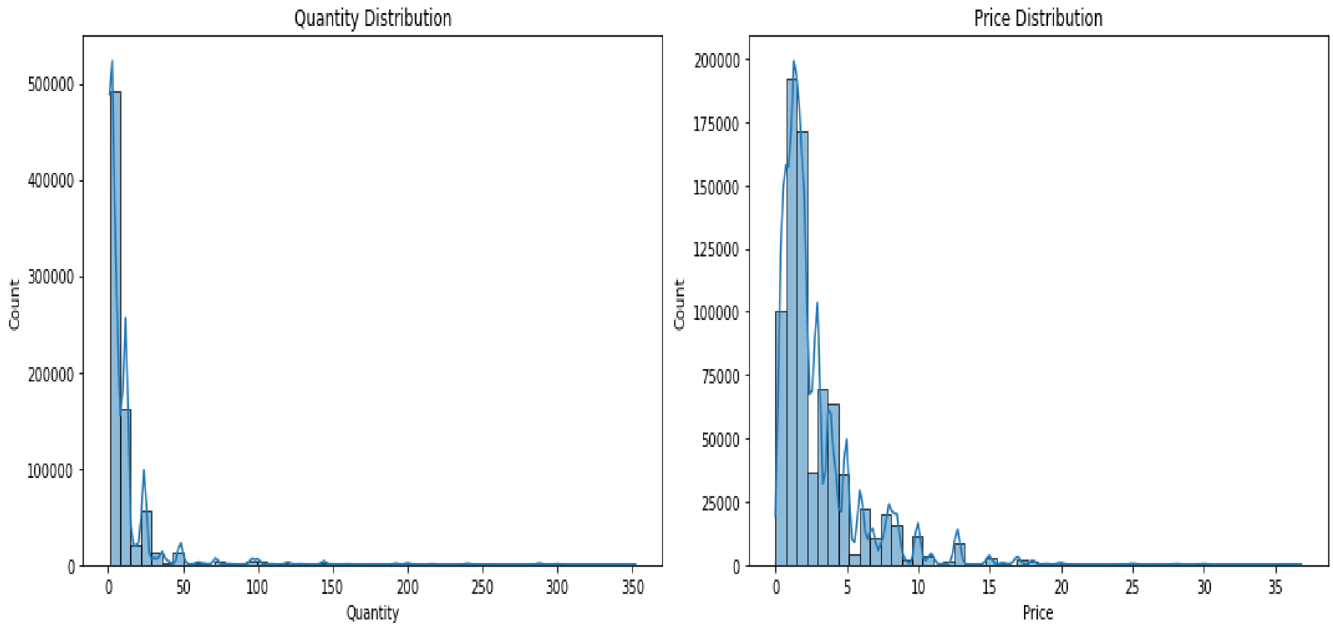
```
df.describe()
```

```
            Quantity          Price    Customer ID
count  776391.000000  776391.000000  776391.000000
mean       11.345298       2.898952   15320.595952
std        22.899219       2.926694    1694.942599
min         1.000000       0.000000   12346.000000
25%         2.000000       1.250000   13974.000000
50%         6.000000       1.950000   15249.000000
75%        12.000000       3.750000   16794.000000
max       352.000000      36.800000   18287.000000
```

```
#Final shape of the dataset
print(f' Final shape of the dataset : {df.shape}')
```

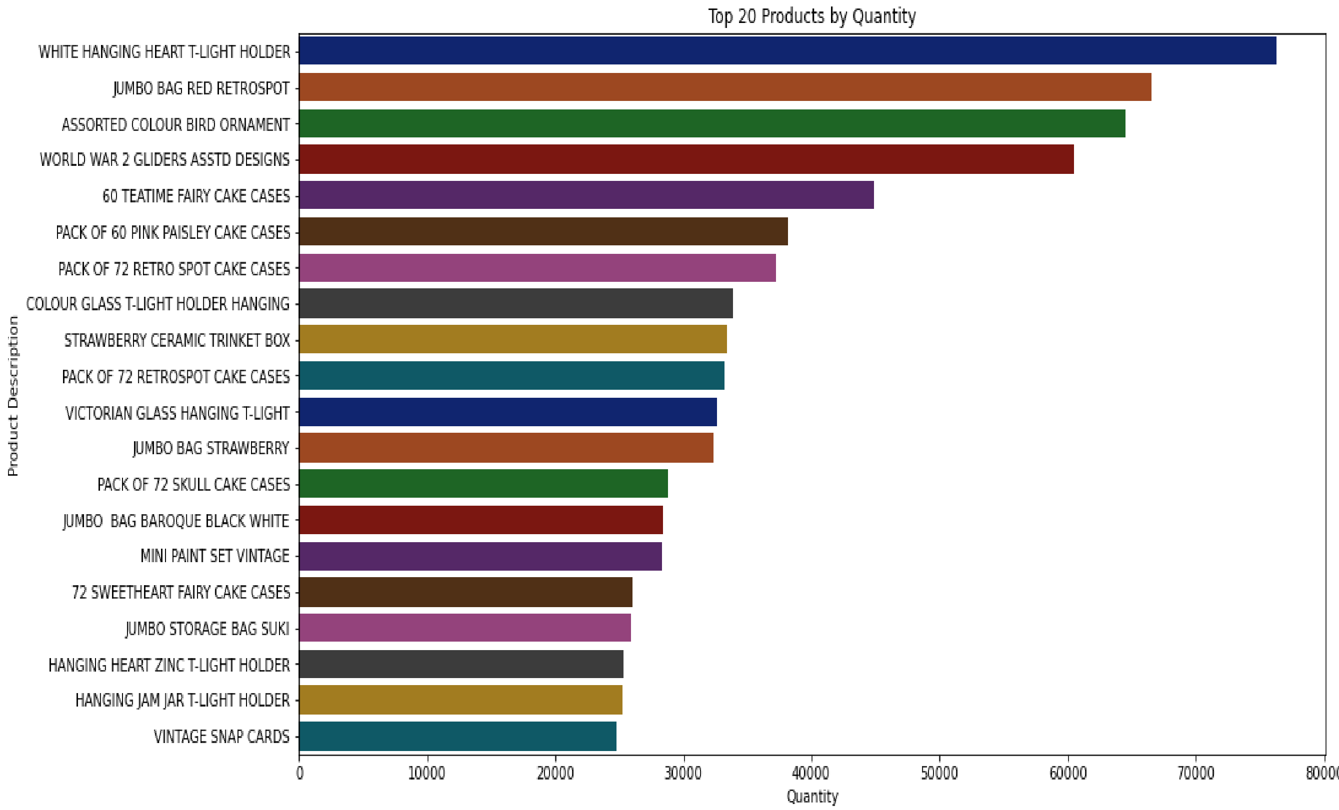
```
 Final shape of the dataset : (776391, 8)
```

```
#Exploratory Data Analysis
figs, axes = plt.subplots(1, 2, figsize=(15, 5))
sns.histplot(df['Quantity'], bins = 50, kde = True, ax = axes[0])
axes[0].set_title('Quantity Distribution')

sns.histplot(df['Price'], bins = 50, kde = True, ax = axes[1])
axes[1].set_title('Price Distribution')

plt.tight_layout()
plt.show()
```

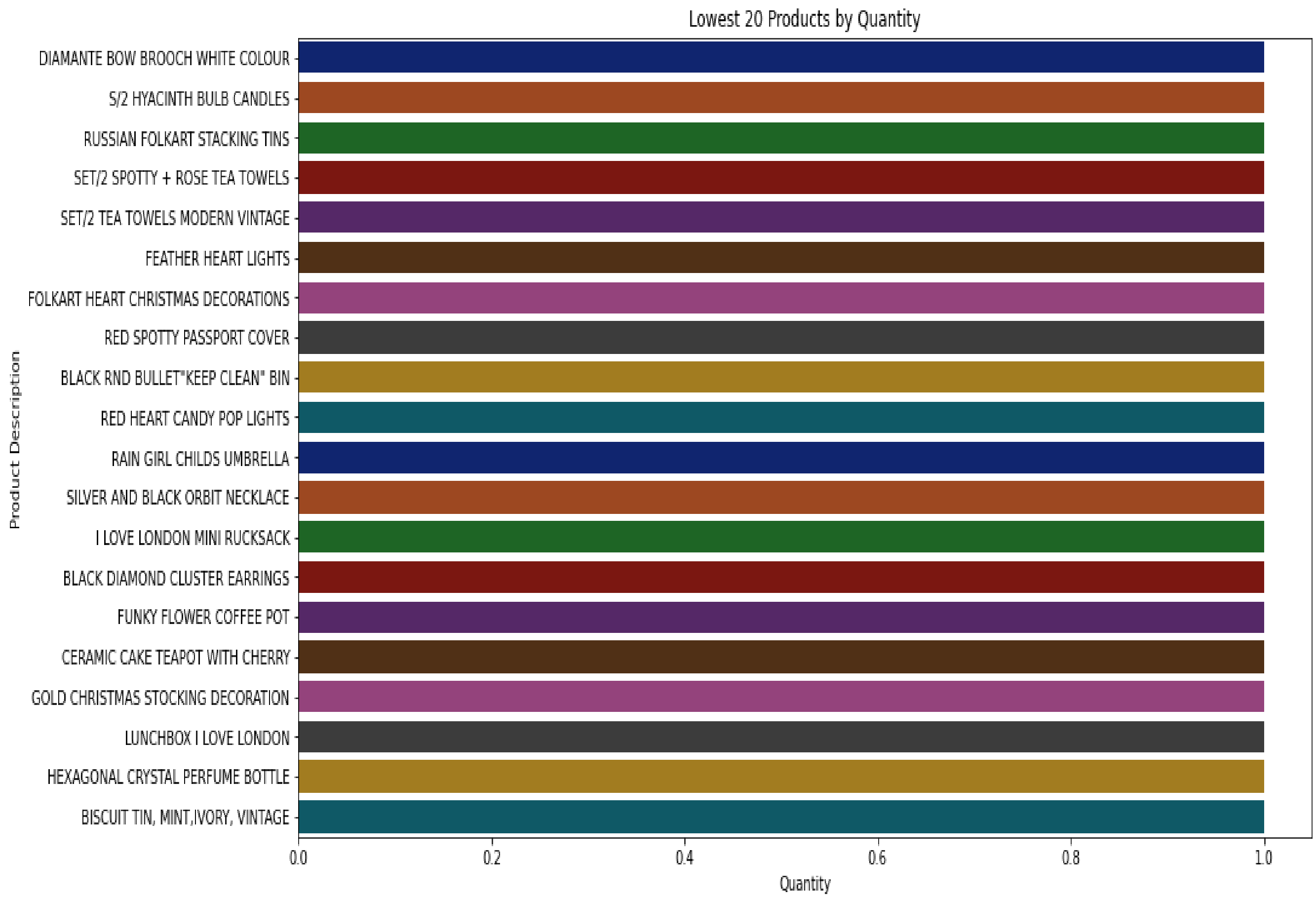


- We can see that the consumers buy things in lower quantity more (especially in the range of 1 - 10)
- Also, the consumers tend to buy more things in the lower price range

```
#Top 20 products based on quantities sold
product_quantity =
df.groupby(df['Description'])['Quantity'].sum().reset_index()
sorted_product_quantity = product_quantity.sort_values(by = 'Quantity',
ascending = False)
# Let's get the top 20 products that are brought by consumers
top_20_products = sorted_product_quantity.head(20)

# Plot the bar plot
plt.figure(figsize=(15, 8))
sns.barplot(x='Quantity', y='Description', data=top_20_products,
palette='dark')
plt.title(f'Top 20 Products by Quantity')
plt.xlabel('Quantity')
plt.ylabel('Product Description')
plt.show()
```




```python
#Least sold products
product_quantity =
df.groupby(df['Description'])['Quantity'].sum().reset_index()
sorted_product_quantity = product_quantity.sort_values(by = 'Quantity',
ascending = True)
# Let's get the top 20 products that are brought by consumers
low_20_products = sorted_product_quantity.head(20)

# Plot the bar plot
plt.figure(figsize=(15, 8))
sns.barplot(x='Quantity', y='Description', data=low_20_products,
palette='dark')
plt.title(f'Lowest 20 Products by Quantity')
plt.xlabel('Quantity')
plt.ylabel('Product Description')
plt.show()
```

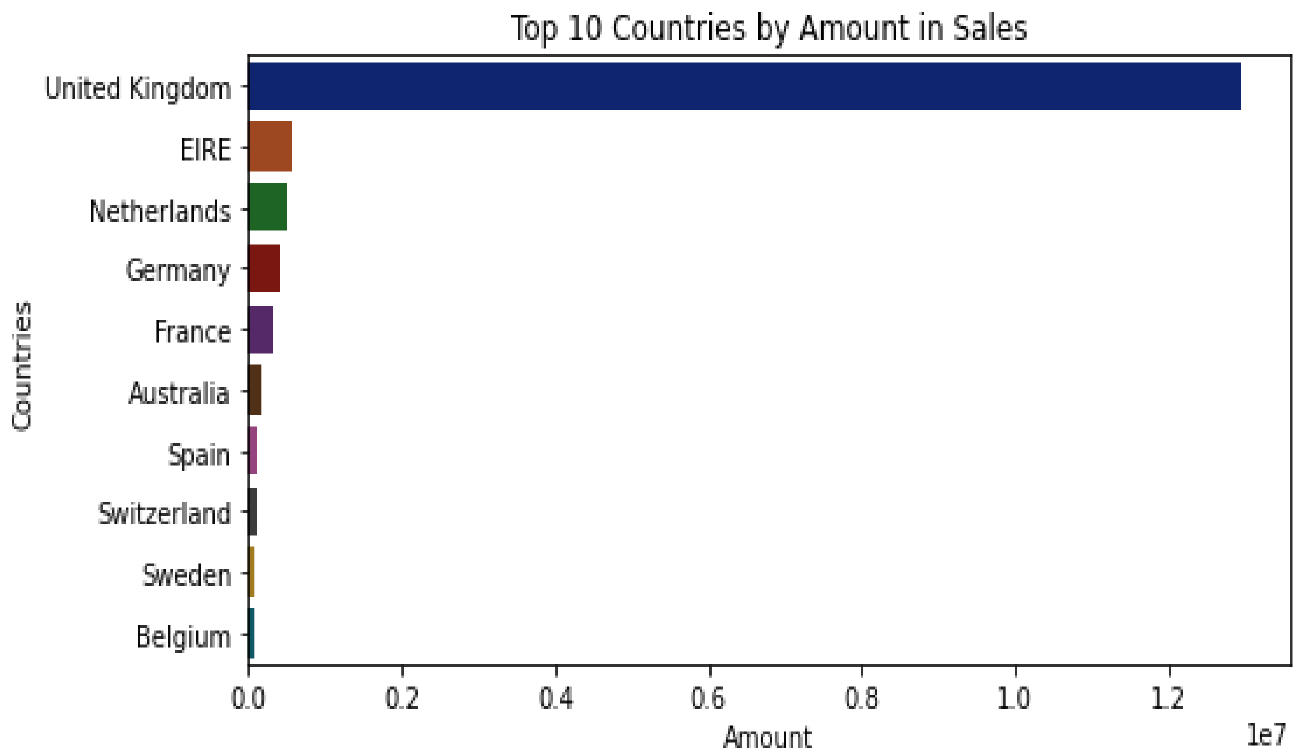



```
#Top 10 countries based on total transactions and amount spent in sales
df['Amount'] = df['Quantity'] * df['Price']

country_sales = df.groupby('Country')['Amount'].sum().reset_index()
country_sales = country_sales.sort_values(by = 'Amount', ascending=False)
top_10_country_sales = country_sales.head(10)
top_10_country_sales
```

```
           Country        Amount
38  United Kingdom  1.293315e+07
10            EIRE  5.611988e+05
24     Netherlands  5.044959e+05
14         Germany  4.182632e+05
13          France  3.181182e+05
0        Australia  1.585301e+05
32           Spain  9.383353e+04
34     Switzerland  9.341204e+04
33          Sweden  7.437688e+04
3          Belgium  6.336422e+04
```

```
# Plot the bar plot
plt.figure(figsize=(8, 4))
sns.barplot(x='Amount', y='Country', data=top_10_country_sales,
```

```
palette='dark')
plt.title(f'Top 10 Countries by Amount in Sales')
plt.xlabel('Amount')
plt.ylabel('Countries')
plt.show()
```

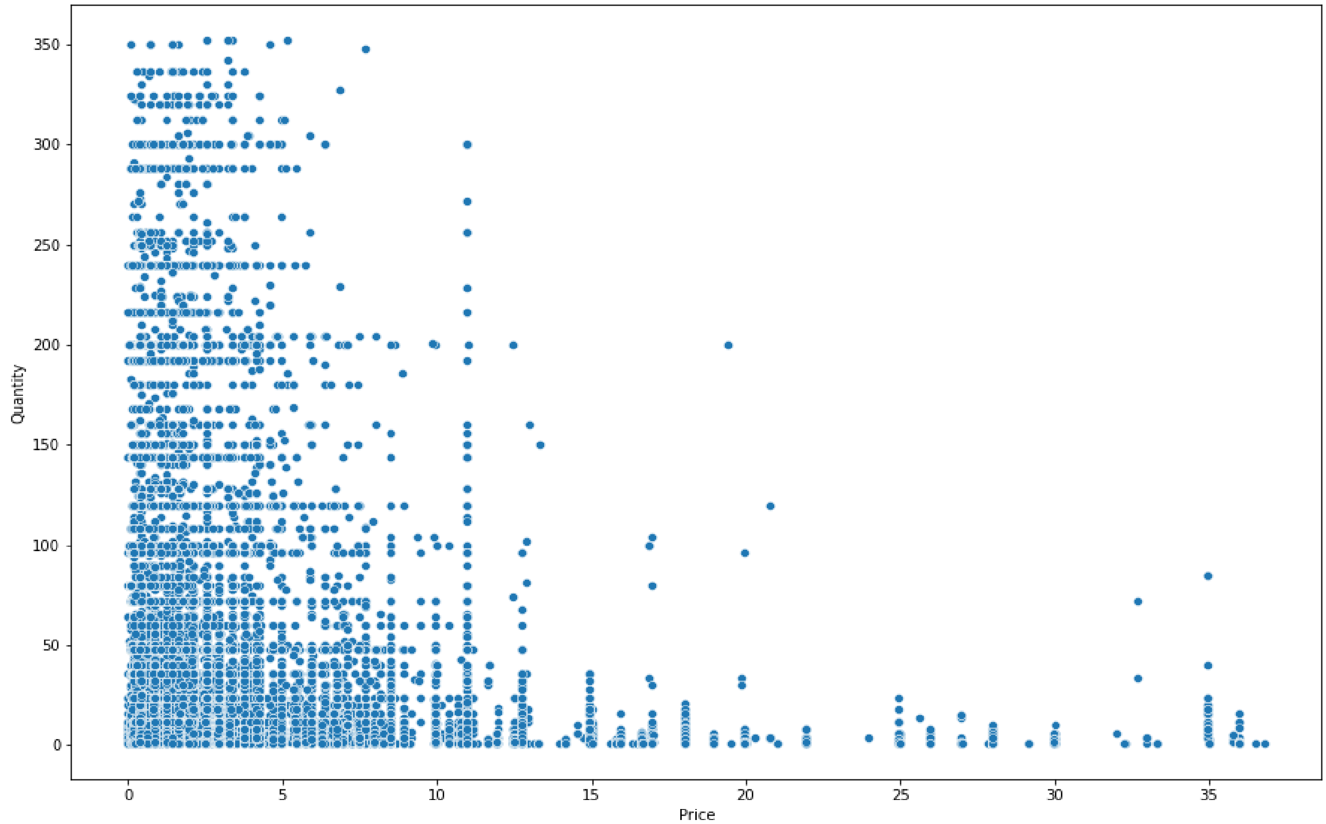



```
from scipy.stats import pearsonr

# Calculate the Pearson correlation coefficient
correlation_coefficient, _ = pearsonr(df['Quantity'], df['Price'])

print(f"Pearson Correlation Coefficient: {correlation_coefficient}")
# Interpretation
if correlation_coefficient > 0:
    print("There is a positive correlation between Quantity and Price.")
elif correlation_coefficient < 0:
    print("There is a negative correlation between Quantity and Price.")
else:
    print("There is no correlation between Quantity and Price.")
```

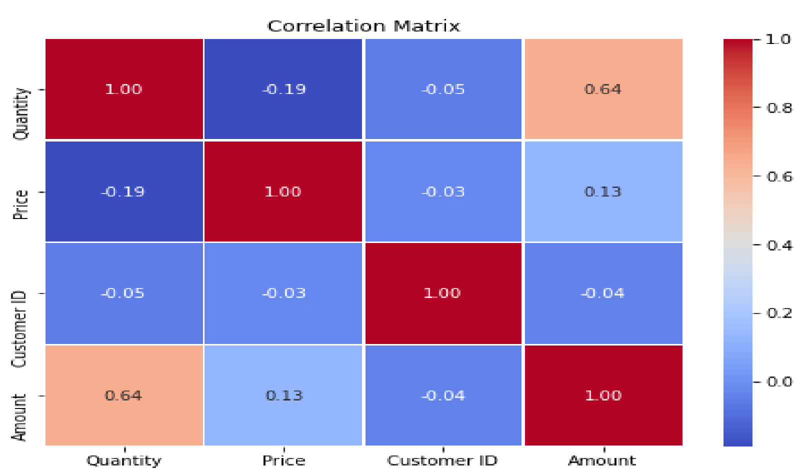
```
Pearson Correlation Coefficient: -0.1904679512762879
There is a negative correlation between Quantity and Price.
```

This makes sense as well, because as the price of a product increases consumers tend to buy lower quantities of the product.

```
plt.figure(figsize = (15,10))
sns.scatterplot(data = df, x = df['Price'], y = df['Quantity'])
plt.show()
```




```
plt.figure(figsize=(8, 6))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f',
linewidths=0.5)
plt.title('Correlation Matrix')
plt.show()
```



There doesn't seem to be any correlation majorly between any variables. There is significant correlation between Quantity and Amount because Amount was derived using Quantity and Price.

RFM (Recency-Frequency-Monetary) analysis is a simple technique for behavior based customer segmentation. It groups customers based on their transaction history – how recently, how often and how much did they buy. It is a handy method to find the best customers, understand their behavior and then run targeted marketing campaigns to increase sales, satisfaction and customer lifetime value.

Customer segmentation is the practice of grouping customers based on common characteristics. These customer segments are beneficial in marketing campaigns, in identifying potentially profitable customers, and in developing customer loyalty. A company might segment customers according to a wide range of factors, including: demographics (age, gender, location etc), behaviour (previous orders, responses to messaging), psychographics (values, interests, lifestyles) etc.

```
# Calculating RFM metrics
current_date = max(df['InvoiceDate'])  # Current date

# Calculate Recency, Frequency, and Monetary metrics for each customer
rfm_df = df.groupby('Customer ID').agg({
    'InvoiceDate': lambda x: (current_date - x.max()).days,  # Recency
    'Invoice': 'nunique',  # Frequency
    'Amount': 'sum'  # Monetary value
})

# Rename columns
rfm_df.rename(columns={
    'InvoiceDate': 'Recency',
    'Invoice': 'Frequency',
    'Amount': 'Monetary'
}, inplace=True)
```

```python
# Print the first few rows of the RFM DataFrame
rfm_df = rfm_df.sort_values(by = 'Monetary',ascending = False)
rfm_df.head()
```

```
             Recency  Frequency   Monetary
Customer ID
14646.0            1        146  480051.24
18102.0            0        134  431479.14
14156.0            9        146  279373.90
14911.0            0        376  270586.49
13694.0            3        136  183223.01
```

We are sorting them in descending order of Monetary value as the Monetary aspect is a crucial component of RFM analysis as it helps segment customers based on their purchasing behavior and contribution to revenue. Customers who spend more tend to be more valuable to a business, and identifying these high-value customers can assist in targeted marketing strategies, loyalty programs, and personalized offerings to maximize revenue and customer retention.

```python
def create_segments(row):
    if row['Recency'] <= 30 and row['Frequency'] >= 100 and row['Monetary']
>= 50000:
        return 'High-Value Customer'
    elif row['Recency'] > 90 and row['Frequency'] < 3:
        return 'Churn Risk'
    else:
        return 'Regular Customer'

rfm_df['Segment'] = rfm_df.apply(create_segments, axis=1)

print("RFM Analysis with Segments:")
rfm_df.head(20)
```

```
RFM Analysis with Segments:

            Recency  Frequency   Monetary              Segment
Customer ID
14646.0            1        146  480051.24  High-Value Customer
18102.0            0        134  431479.14  High-Value Customer
14156.0            9        146  279373.90  High-Value Customer
14911.0            0        376270586.49  High-Value Customer
13694.0            3        136  183223.01  High-Value Customer
17511.0            2         60  171593.92     Regular Customer
12415.0           23         26  134763.45     Regular Customer
16684.0            3         49  120013.25     Regular Customer
```

```
15061.0           3        123  117759.34  High-Value Customer
15311.0           0        208  114706.42  High-Value Customer
13089.0           2        202  113297.06  High-Value Customer
17450.0           7         44   90449.63     Regular Customer
14298.0           7         79   89807.15     Regular Customer
16029.0          38        103   78038.63     Regular Customer
13798.0           0        110   75260.39  High-Value Customer
17841.0           1        211   67101.05  High-Value Customer
15769.0           6         44   65333.52     Regular Customer
14088.0           9         16   63519.00     Regular Customer
17389.0           0         61   57215.33     Regular Customer
13081.0          11         28   56787.97     Regular Customer
```

This was one way to do this. Now we will be trying another method where we convert these values to the range from 1 to 5 across all the metrics for easier segmentation and for having a consistent range across all the metrics

Customers with the highest RFM score is considered the "best" customer. They have made recent purchases (high R), engage frequently (high F), and contribute significantly in terms of monetary value (high M). These customers are often considered the most valuable and important for the business.

```
r_labels, f_labels, m_labels = range(1, 6), range(1,6), range(1,6)
# Define custom bins (adjust according to your data distribution)
custom_bins = [0, 5, 10, 20, 30, 1000]

# Use pd.cut() with custom bins
rfm_df['r_score'] = pd.qcut(rfm_df['Recency'], q=5,
labels=r_labels).astype(int)
rfm_df['f_score'] = pd.cut(rfm_df['Frequency'], bins=custom_bins,
labels=f_labels).astype(int)
rfm_df['m_score'] = pd.qcut(rfm_df['Monetary'], q=5,
labels=m_labels).astype(int)

rfm_df['rfm_sum'] = rfm_df['r_score'] + rfm_df['m_score'] + rfm_df['f_score']
rfm_df = rfm_df.sort_values(by = "rfm_sum",ascending = False)
rfm_df
```

```
             Recency  Frequency  Monetary           Segment  r_score  f_score
\
Customer ID
12835.0          427         41   5996.83  Regular Customer        5        5
17448.0          496         46  14523.67  Regular Customer        5        5
17850.0          371        155  51208.87  Regular Customer        4        5
13564.0          353         36  15818.33  Regular Customer        4        5
```

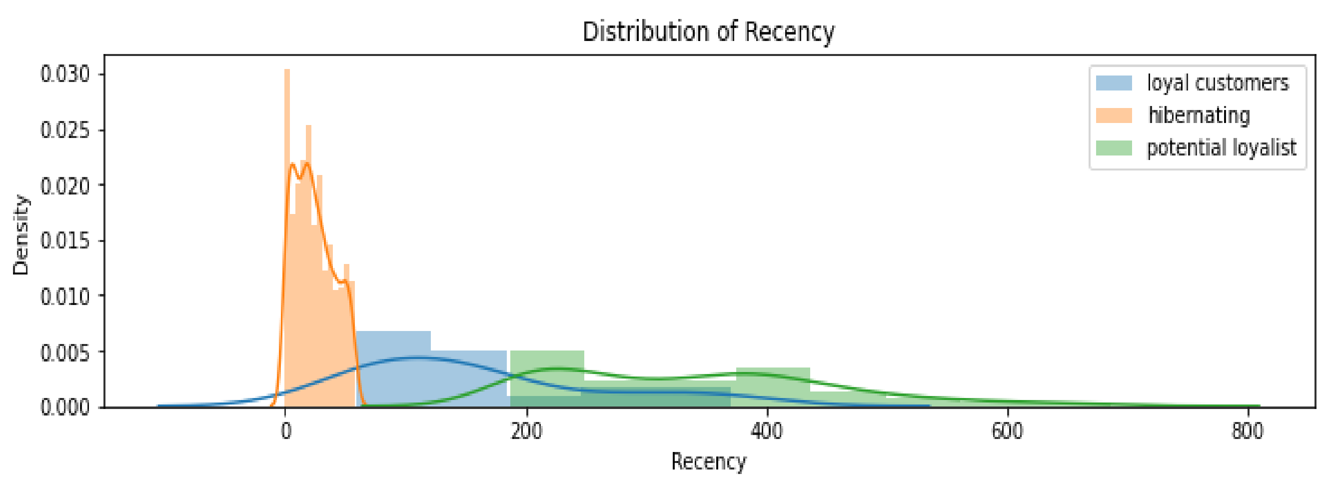
```
13093.0          275        55  54144.25  Regular Customer        4        5
...              ...       ...       ...               ...      ...      ...
18249.0           16         1     95.34  Regular Customer        1        1
14578.0            2         1    168.63  Regular Customer        1        1
17737.0            8         2    168.24  Regular Customer        1        1
17385.0           14         1    256.11  Regular Customer        1        1
13189.0           18         2    260.68  Regular Customer        1        1

             m_score  rfm_sum
Customer ID
12835.0            5       15
17448.0            5       15
17850.0            5       14
13564.0            5       14
13093.0            5       14
...              ...      ...
18249.0            1        3
14578.0            1        3
17737.0            1        3
17385.0            1        3
13189.0            1        3

[5834 rows x 8 columns]
```

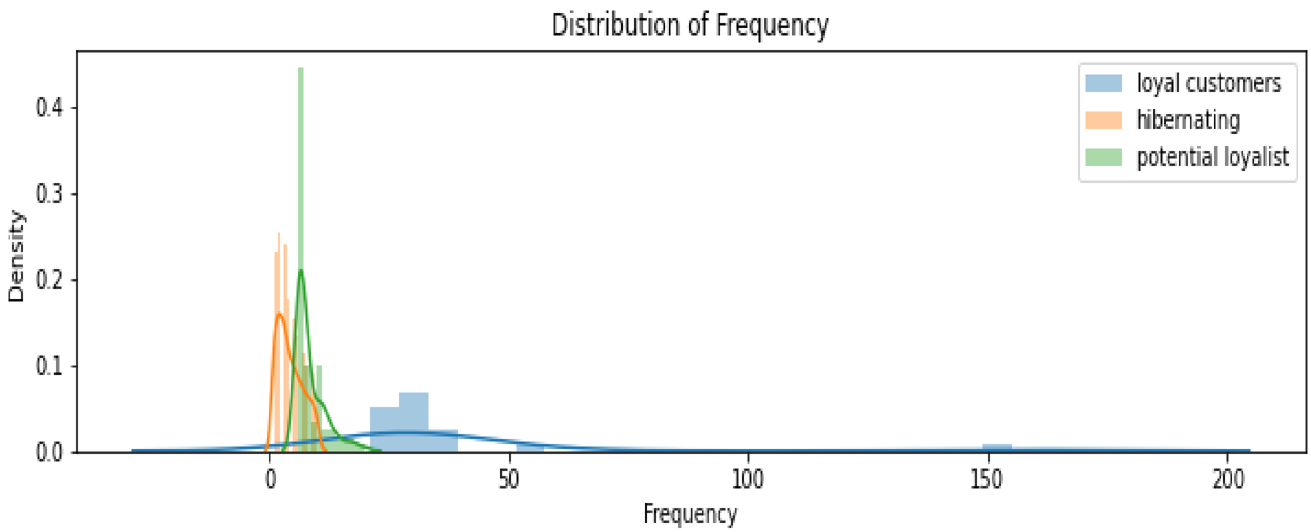
```
def assign_label(df, r_rule, fm_rule, label, colname='rfm_label'):
    df.loc[(df['r_score'].between(r_rule[0], r_rule[1]))
            & (df['f_score'].between(fm_rule[0], fm_rule[1])), colname] =
label
    return df

rfm_df['rfm_label'] = ''

rfm_df = assign_label(rfm_df, (5,5), (4,5), 'champions')
rfm_df = assign_label(rfm_df, (3,4), (4,5), 'loyal customers')
rfm_df = assign_label(rfm_df, (4,5), (2,3), 'potential loyalist')
rfm_df = assign_label(rfm_df, (5,5), (1,1), 'new customers')
rfm_df = assign_label(rfm_df, (4,4), (1,1), 'promising')
rfm_df = assign_label(rfm_df, (3,3), (3,3), 'needing attention')
rfm_df = assign_label(rfm_df, (3,3), (1,2), 'about to sleep')
rfm_df = assign_label(rfm_df, (1,2), (3,4), 'at risk')
rfm_df = assign_label(rfm_df, (1,2), (5,5), 'cant loose them')
rfm_df = assign_label(rfm_df, (1,2), (1,2), 'hibernating')
rfm_df
```

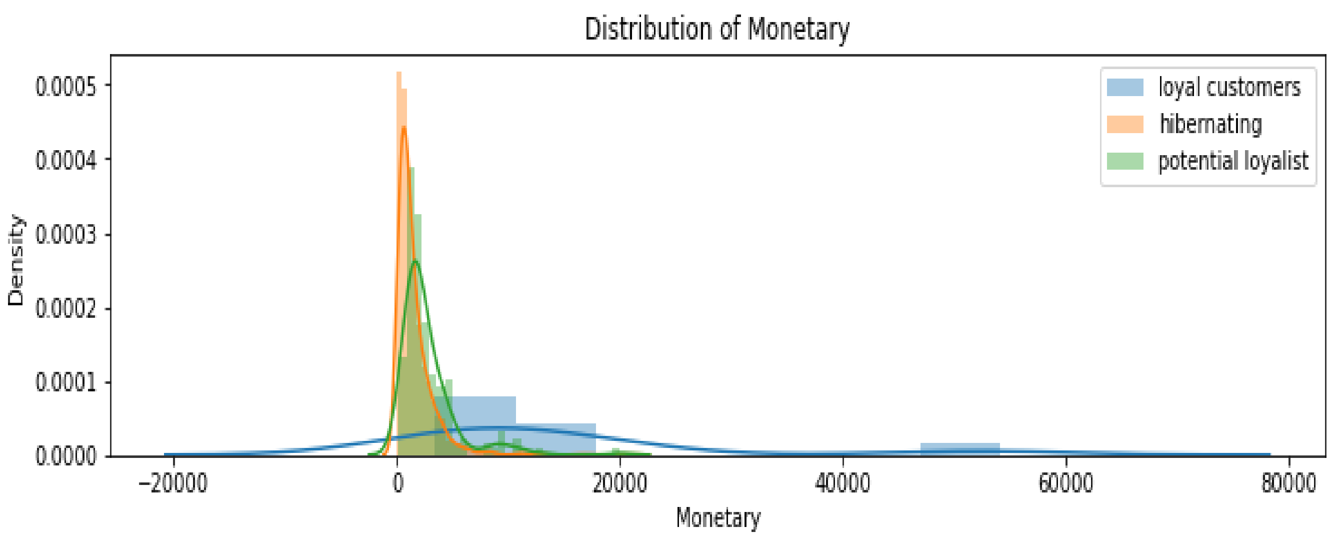
```
             Recency  Frequency  Monetary           Segment  r_score  f_score
\
Customer ID
12835.0          427         41   5996.83  Regular Customer        5        5
17448.0          496         46  14523.67  Regular Customer        5        5
17850.0          371        155  51208.87  Regular Customer        4        5
```

```
13564.0         353         36  15818.33  Regular Customer        4        5
13093.0         275         55  54144.25  Regular Customer        4        5
...             ...        ...       ...               ...      ...      ...
18249.0          16          1     95.34  Regular Customer        1        1
14578.0           2          1    168.63  Regular Customer        1        1
17737.0           8          2    168.24  Regular Customer        1        1
17385.0          14          1    256.11  Regular Customer        1        1
13189.0          18          2    260.68  Regular Customer        1        1

             m_score  rfm_sum        rfm_label
Customer ID
12835.0            5       15        champions
17448.0            5       15        champions
17850.0            5       14  loyal customers
13564.0            5       14  loyal customers
13093.0            5       14  loyal customers
...              ...      ...              ...
18249.0            1        3      hibernating
14578.0            1        3      hibernating
17737.0            1        3      hibernating
17385.0            1        3      hibernating
13189.0            1        3      hibernating

[5834 rows x 9 columns]
```

```python
segments = ['loyal customers', 'hibernating', 'potential loyalist']

for col in ['Recency','Frequency','Monetary']:
    fig, ax = plt.subplots(figsize=(12,3))
    for segment in segments:
        sns.distplot(rfm_df[rfm_df['rfm_label']==segment][col],
label=segment)
    ax.set_title('Distribution of %s' % col)
    plt.legend()
    plt.show()
```







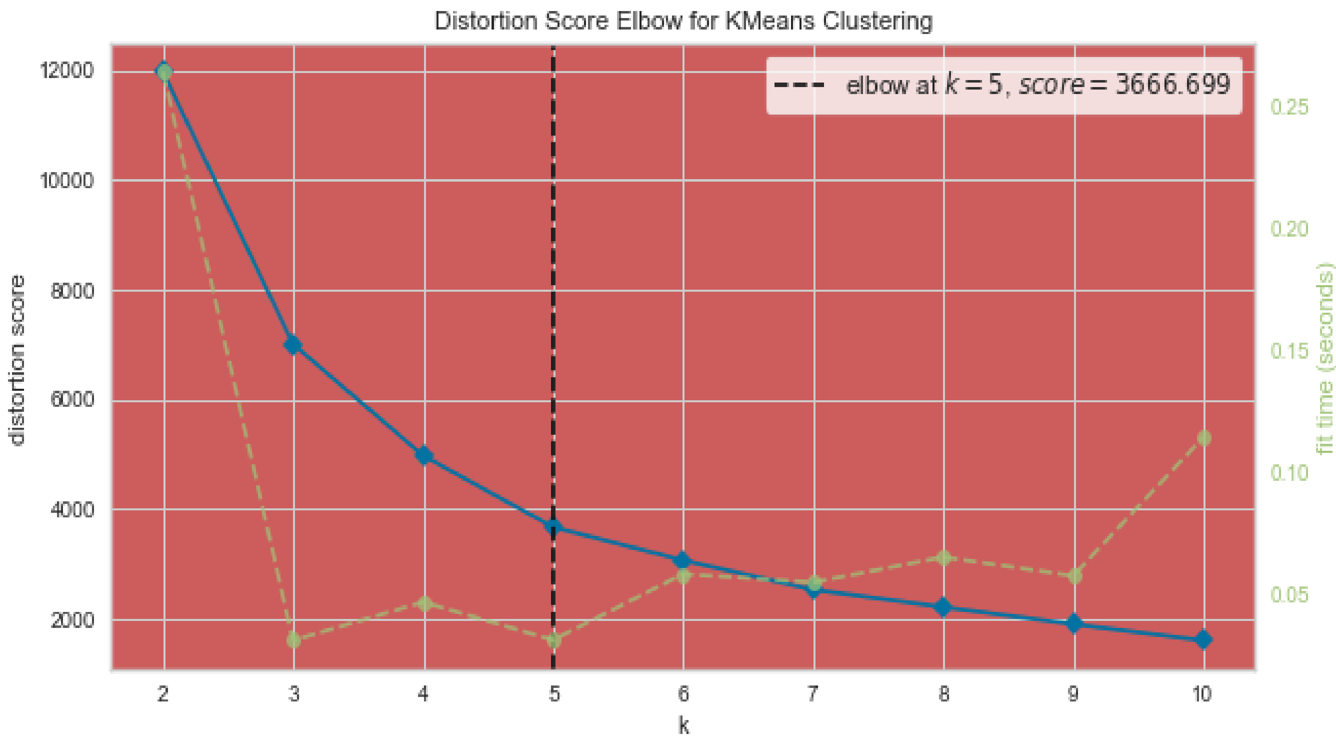

```
#K-Means Clustering for customer segmentation

cluster_df = pd.DataFrame()
for i in ['Recency','Frequency','Monetary']:
    cluster_df[i] = rfm_df[i]
cluster_df

             Recency  Frequency  Monetary
Customer ID
```

```
12835.0          427         41   5996.83
17448.0          496         46  14523.67
17850.0          371        155  51208.87
13564.0          353         36  15818.33
13093.0          275         55  54144.25
...              ...        ...        ...
18249.0           16          1     95.34
14578.0            2          1    168.63
17737.0            8          2    168.24
17385.0           14          1    256.11
13189.0           18          2    260.68

[5834 rows x 3 columns]
```

```python
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
rfm_cluster_scaled = scaler.fit_transform(cluster_df)
rfm_cluster_scaled
```

```
array([[ 1.08982186,  2.74098725,  0.27674209],
       [ 1.42037469,  3.13526791,  0.98779456],
       [ 0.8215471 , 11.73058631,  4.0469703 ],
       ...,
       [-0.9174482 , -0.3344019 , -0.20930354],
       [-0.88870448, -0.41325804, -0.20197607],
       [-0.869542  , -0.3344019 , -0.20159497]])
```

```python
from sklearn.cluster import KMeans
from yellowbrick.cluster import KElbowVisualizer

# Finding initial K value using Elbow Method
plt.figure(figsize=(10,5))
ax = plt.axes()
ax.set_facecolor("#cd5c5c")
Elbow_M = KElbowVisualizer(KMeans(), k=10)
Elbow_M.fit(rfm_cluster_scaled)
Elbow_M.show()
```




```
kmeans = KMeans(n_clusters = 5,max_iter = 50)
kmeans.fit(rfm_cluster_scaled)
```

```
KMeans(max_iter=50, n_clusters=5)
```

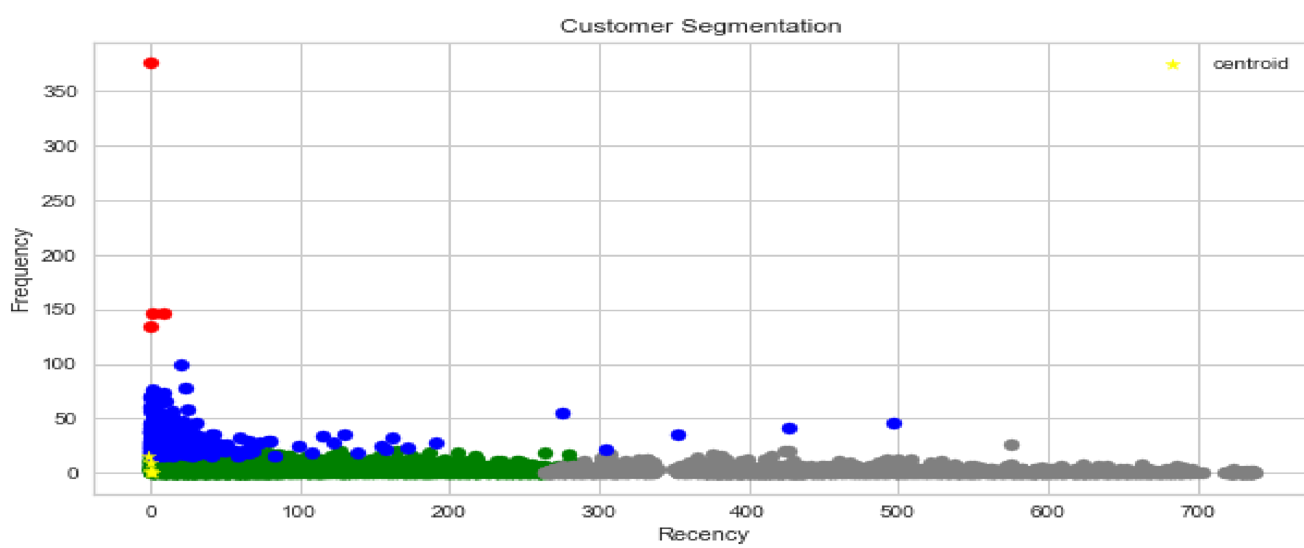
```
cluster_df['Clusters'] = kmeans.labels_
cluster_df
```

```
             Recency  Frequency  Monetary  Clusters
Customer ID
12835.0          427         41   5996.83         3
17448.0          496         46  14523.67         3
17850.0          371        155  51208.87         4
13564.0          353         36  15818.33         3
13093.0          275         55  54144.25         3
...              ...        ...       ...       ...
18249.0           16          1     95.34         0
14578.0            2          1    168.63         0
17737.0            8          2    168.24         0
17385.0           14          1    256.11         0
13189.0           18          2    260.68         0

[5834 rows x 4 columns]
```

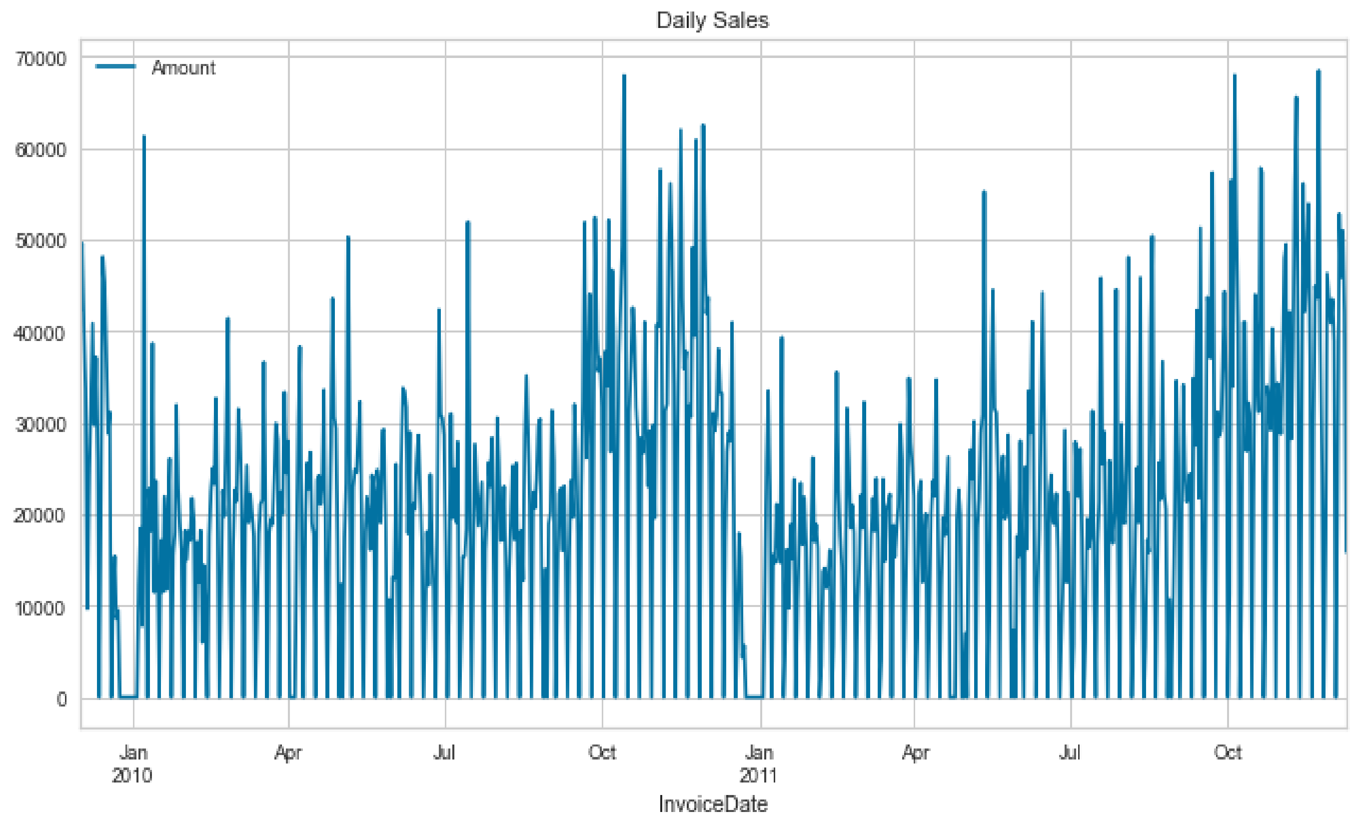
```python
# Centroids of the clusters
kmeans.cluster_centers_
```

```
array([[-0.60480772, -0.0772999 , -0.06824749],
       [-0.94379662, 15.31854032, 30.24506502],
       [ 1.28295517, -0.3195366 , -0.16649439],
       [-0.84561741,  1.89445728,  0.93238793],
       [-0.83373841,  9.96254882,  6.712379  ]])
```

```python
# grouping the data in accorandance with each cluster seperately
one = cluster_df[cluster_df["Clusters"]==0]
two = cluster_df[cluster_df["Clusters"]==1]
three = cluster_df[cluster_df["Clusters"]==2]
four = cluster_df[cluster_df["Clusters"]==3]
five = cluster_df[cluster_df['Clusters']==4]

#Checking the quality of clustering in the data set
plt.figure(figsize=(10,5))
ax = plt.axes()
plt.scatter(one["Recency"],one["Frequency"],color='green')
plt.scatter(two["Recency"],two["Frequency"],color='red')
plt.scatter(three["Recency"],three["Frequency"],color='grey')
plt.scatter(four["Recency"],four["Frequency"],color='blue')
plt.scatter(kmeans.cluster_centers_[:,0],kmeans.cluster_centers_[:,1],color="
yellow",marker="*",label="centroid")
plt.xlabel('Recency')
plt.ylabel('Frequency')
plt.title('Customer Segmentation')
plt.legend()
plt.show ()
```

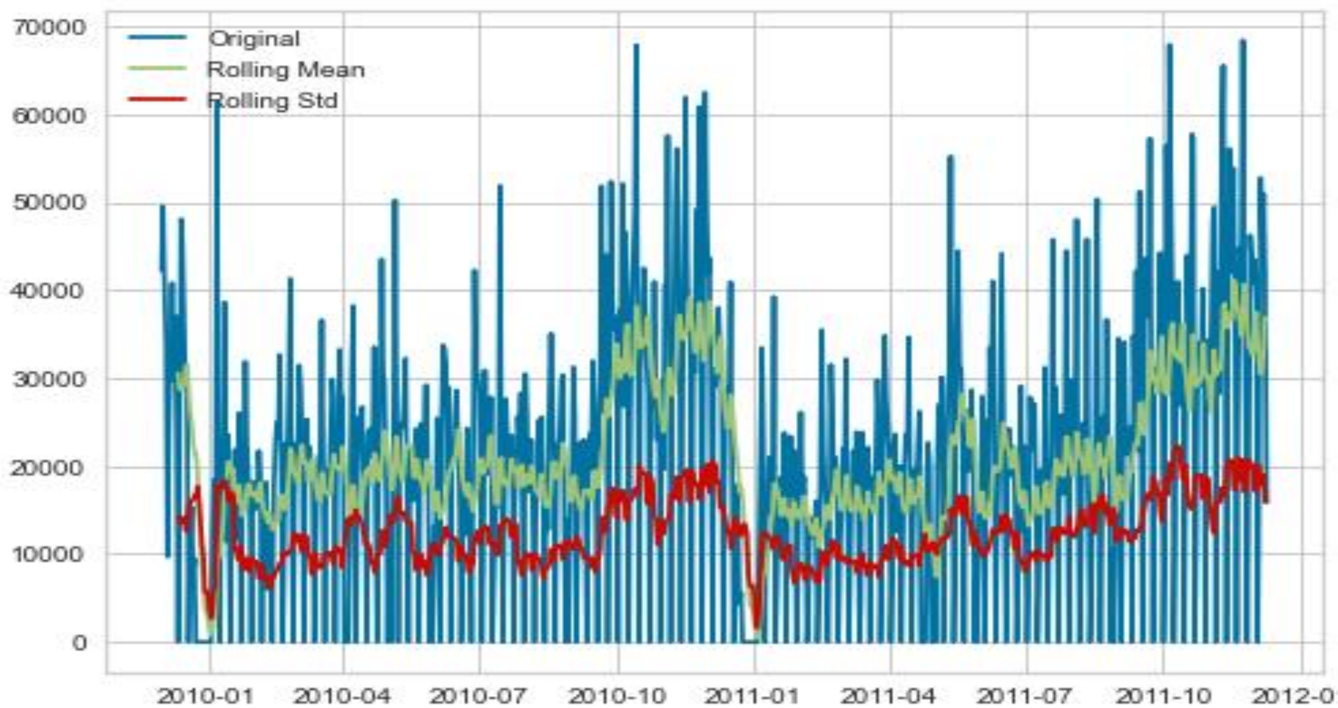


```python
#Checking stationarity

# Extracting relevant columns for time series analysis
time_series_data = df[['InvoiceDate', 'Amount']]

# Set 'InvoiceDate' as the index
time_series_data.set_index('InvoiceDate', inplace=True)

# Resample data by a specific frequency (e.g., daily)
resampled_data = time_series_data.resample('D').sum()

# Plot the resampled data
resampled_data.plot(figsize=(12, 6), title='Daily Sales')
plt.show()
```




```python
from statsmodels.tsa.stattools import adfuller

def test_stationarity(timeseries):
    # Plot rolling statistics
    rolling_mean = timeseries.rolling(window=12).mean()
    rolling_std = timeseries.rolling(window=12).std()
    plt.plot(figsize=(12,8))
    plt.plot(timeseries, label='Original')
    plt.plot(rolling_mean, label='Rolling Mean')
    plt.plot(rolling_std, label='Rolling Std')
```

```
    plt.legend()
    plt.show()

    # Perform ADF test
    result = adfuller(timeseries)
    print('ADF Statistic:', result[0])
    print('p-value:', result[1])
    print('Critical Values:', result[4])

# Check stationarity
test_stationarity(resampled_data['Amount'])
```

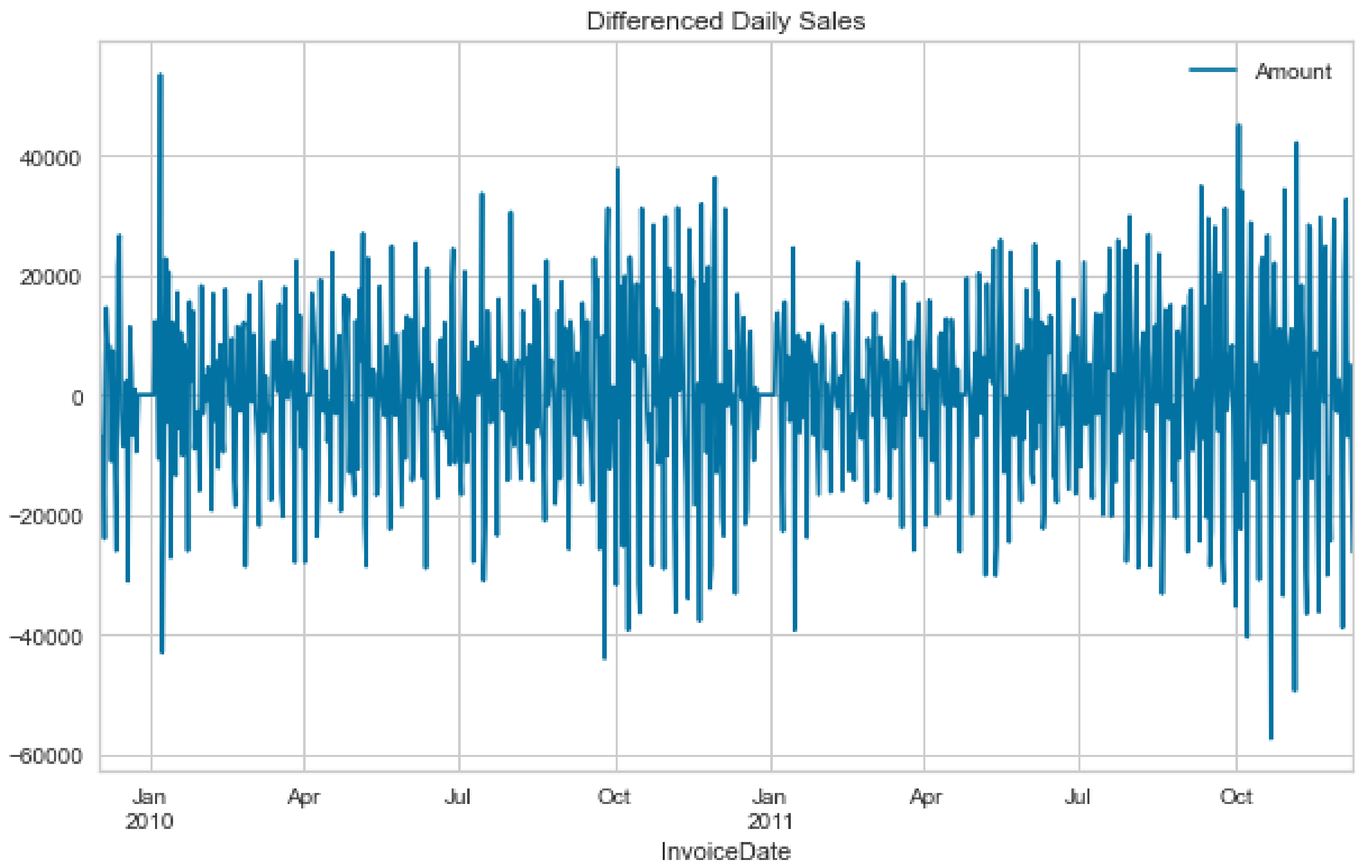



```
ADF Statistic: -2.6324236497324636
p-value: 0.0864793920275096
Critical Values: {'1%': -3.439490435810785, '5%': -2.8655738086413374, '10%':
-2.568918067209286}
```

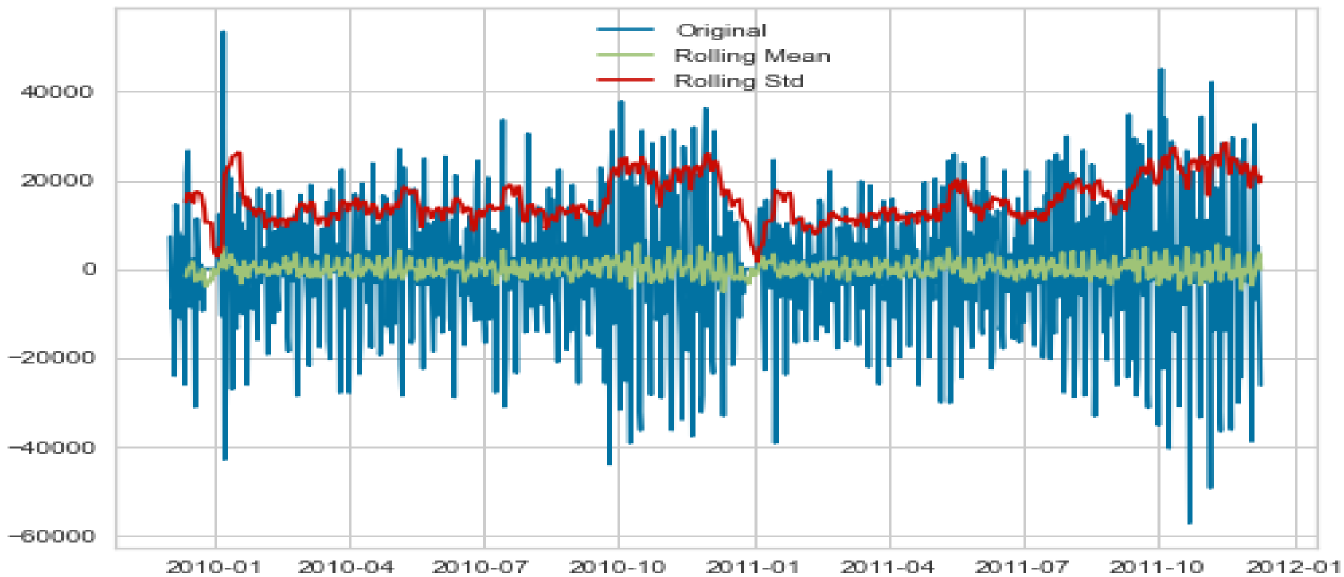
ADF Statistic (-2.63) is greater than the critical values at the 1% and 5% levels but less than the critical value at the 10% level.
p-value (0.089) is greater than the common significance level of 0.05.

```
# Make the time series stationary through differencing
resampled_data_diff = resampled_data.diff().dropna()
```

```python
# Plot the differenced data
resampled_data_diff.plot(figsize=(10, 6), title='Differenced Daily Sales')
plt.show()
```




```python
# Check stationarity again
test_stationarity(resampled_data_diff['Amount'])
```

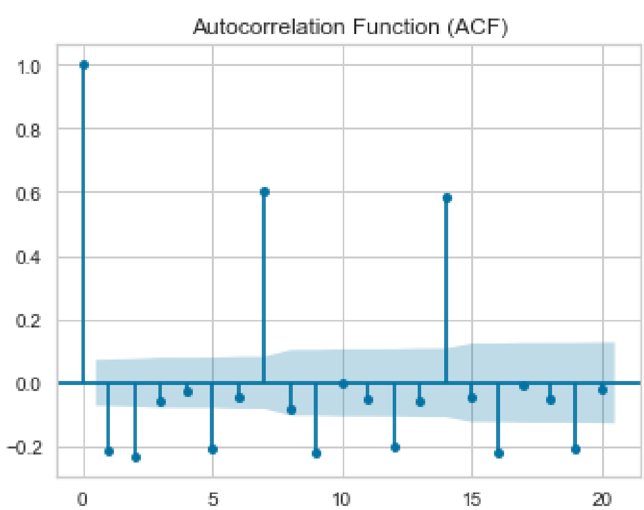


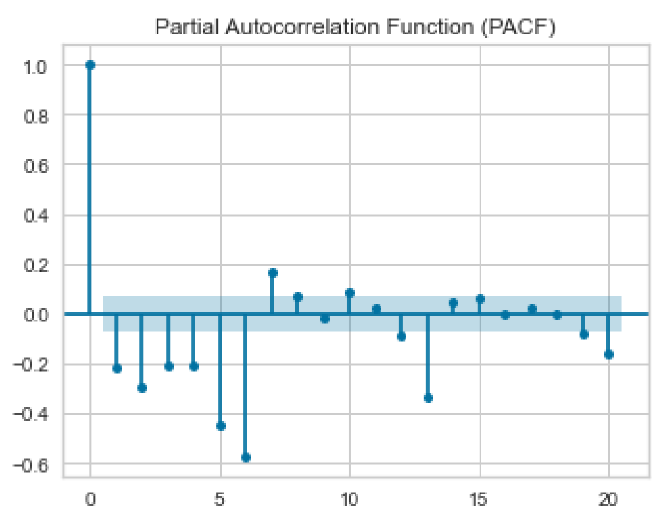
```
ADF Statistic: -9.79982237755707
p-value: 6.036754252973782e-17
Critical Values: {'1%': -3.439490435810785, '5%': -2.8655738086413374, '10%':
-2.568918067209286}
```

ADF Statistic: The ADF Statistic is significantly lower than the critical values at all common significance levels (1%, 5%, 10%). This suggests strong evidence against the null hypothesis of non-stationarity.
p-value: The p-value is extremely small (close to zero), providing strong evidence against the null hypothesis.

Conclusion: Based on these results, you can confidently say that the time series is now stationary after differencing.

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
import time

# Plot ACF and PACF to determine ARIMA parameters
fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))

# ACF plot
plot_acf(resampled_data_diff, lags=20, ax=ax1)
ax1.set_title('Autocorrelation Function (ACF)')

# PACF plot
plot_pacf(resampled_data_diff, lags=20, ax=ax2)
ax2.set_title('Partial Autocorrelation Function (PACF)')

plt.show()
```

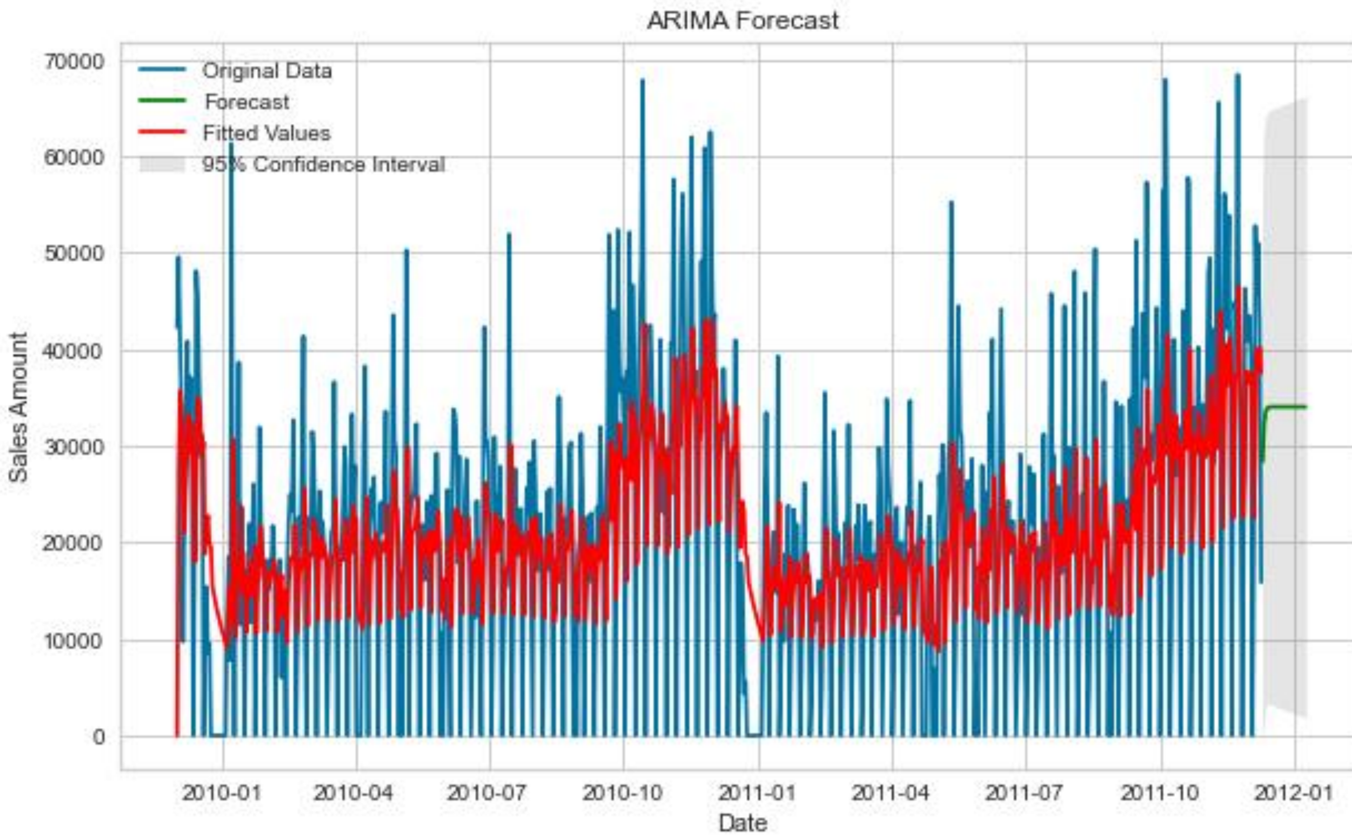




The ACF shows significant spikes at lag 1, indicating that the series is still autocorrelated after differencing.

The PACF plot shows significant spikes at lags 1 and possibly lag 2, indicating the presence of autoregressive components up to lag 2. This suggests that an ARIMA model with an AR term of 1 or 2 might be appropriate.

```
# Build ARIMA model
p, d, q = 1, 1, 1  # Adjust parameters based on your plots
model = ARIMA(resampled_data, order=(p, d, q))
results = model.fit()

# Make forecasts
forecast_steps = 30  # Adjust as needed
forecast = results.get_forecast(steps=forecast_steps)
forecast_values = forecast.predicted_mean# Visualize results
plt.figure(figsize=(10,6))
plt.plot(resampled_data.index, resampled_data['Amount'], label='Original
Data')
plt.plot(forecast_values.index, forecast_values, color='green',
label='Forecast')
plt.plot(results.fittedvalues.index, results.fittedvalues, color='red',
label='Fitted Values')


# Add confidence intervals
conf_int = forecast.conf_int()
plt.fill_between(conf_int.index, conf_int.iloc[:, 0], conf_int.iloc[:, 1],
color='gray', alpha=0.2, label='95% Confidence Interval')

# Add labels and legend
plt.xlabel('Date')
plt.ylabel('Sales Amount')
plt.title('ARIMA Forecast')
plt.legend()
plt.show()
```



Model Fit: The red line closely follows the blue line, suggesting that the ARIMA model fits the training data reasonably well.

Forecast: The green line indicates the forecasted sales values. It appears to continue the general trend and seasonal pattern observed in the historical data.